1.1 What Is AI?

We have claimed that AI is interesting, but we have not said what it *is*. Historically, researchers have pursued several different versions of AI. Some have defined intelligence in terms of fidelity to *human* performance, while others prefer an abstract, formal definition of intelligence called **rationality**—loosely speaking, doing the "right thing." The subject matter itself also varies: some consider intelligence to be a property of internal *thought processes* and *reasoning*, while others focus on intelligent *behavior*, an external characterization.[1]

1 In the public eye, there is sometimes confusion between the terms "artificial intelligence" and "machine learning." Machine learning is a subfield of AI that studies the ability to improve performance based on experience. Some AI systems use machine learning methods to achieve competence, but some do not.

Rationality

From these two dimensions—human vs. rational[2] and thought vs. behavior—there are four possible combinations, and there have been adherents and research programs for all four. The methods used are necessarily different: the pursuit of human-like intelligence must be in part an empirical science related to psychology, involving observations and hypotheses about actual human behavior and thought processes; a rationalist approach, on the other hand, involves a combination of mathematics and engineering, and connects to statistics, control theory, and economics. The various groups have both disparaged and helped each other. Let us look at the four approaches in more detail.

2 We are not suggesting that humans are "irrational" in the dictionary sense of "deprived of normal mental clarity." We are merely conceding that human decisions are not always mathematically perfect.

1.1.1 Acting humanly: The Turing test approach

Turing test

The **Turing test**, proposed by Alan Turing (1950), was designed as a thought experiment that would sidestep the philosophical vagueness of the question "Can a machine think?" A computer passes the test if a human interrogator, after posing some written questions, cannot tell whether the written responses come from a person or from a computer. Chapter 27 discusses the details of the test and whether a computer would really be intelligent if it passed. For now, we note that programming a computer to pass a rigorously applied test provides plenty to work on. The computer would need the following capabilities:

- **natural language processing** to communicate successfully in a human language;
- **knowledge representation** to store what it knows or hears;
- **automated reasoning** to answer questions and to draw new conclusions;
- **machine learning** to adapt to new circumstances and to detect and extrapolate patterns.

Natural language processing

Knowledge representation

Automated reasoning

Machine learning

Total Turing test

Turing viewed the *physical* simulation of a person as unnecessary to demonstrate intelligence. However, other researchers have proposed a **total Turing test**, which requires interaction with objects and people in the real world. To pass the total Turing test, a robot will need

- **computer vision** and speech recognition to perceive the world;
- **robotics** to manipulate objects and move about.

Computer vision

Robotics

These six disciplines compose most of AI. Yet AI researchers have devoted little effort to passing the Turing test, believing that it is more important to study the underlying principles of intelligence. The quest for "artificial flight" succeeded when engineers and inventors stopped imitating birds and started using wind tunnels and learning about aerodynamics. Aeronautical engineering texts do not define the goal of their field as making "machines that fly so exactly like pigeons that they can fool even other pigeons."

1.1.2 Thinking humanly: The cognitive modeling approach

To say that a program thinks like a human, we must know how humans think. We can learn about human thought in three ways:

- **introspection**—trying to catch our own thoughts as they go by;
- **psychological experiments**—observing a person in action;
- **brain imaging**—observing the brain in action.

Introspection

Psychological experiments

Brain imaging

Once we have a sufficiently precise theory of the mind, it becomes possible to express the theory as a computer program. If the program's input–output behavior matches corresponding human behavior, that is evidence that some of the program's mechanisms could also be operating in humans.

For example, Allen Newell and Herbert Simon, who developed GPS, the "General Problem Solver" (Newell and Simon 1961), were not content merely to have their program solve problems correctly. They were more concerned with comparing the sequence and timing of its reasoning steps to those of human subjects solving the same problems. The interdisciplinary field of **cognitive science** brings together computer models from AI and experimental techniques from psychology to construct precise and testable theories of the human mind.

Cognitive science

Cognitive science is a fascinating field in itself, worthy of several textbooks and at least one encyclopedia (Wilson and Keil 1999). We will occasionally comment on similarities or differences between AI techniques and human cognition. Real cognitive science, however, is necessarily based on experimental investigation of actual humans or animals. We will leave that for other books, as we assume the reader has only a computer for experimentation.

In the early days of AI there was often confusion between the approaches. An author would argue that an algorithm performs well on a task and that it is *therefore* a good model of human performance, or vice versa. Modern authors separate the two kinds of claims; this

distinction has allowed both AI and cognitive science to develop more rapidly. The two fields fertilize each other, most notably in computer vision, which incorporates neurophysiological evidence into computational models. Recently, the combination of neuroimaging methods combined with machine learning techniques for analyzing such data has led to the beginnings of a capability to "read minds"—that is, to ascertain the semantic content of a person's inner thoughts. This capability could, in turn, shed further light on how human cognition works.

1.1.3 Thinking rationally: The "laws of thought" approach

The Greek philosopher Aristotle was one of the first to attempt to codify "right thinking"—that is, irrefutable reasoning processes. His **syllogisms** provided patterns for argument structures that always yielded correct conclusions when given correct premises. The canonical example starts with *Socrates is a man* and *all men are mortal* and concludes that *Socrates is mortal*. (This example is probably due to Sextus Empiricus rather than Aristotle.) These laws of thought were supposed to govern the operation of the mind; their study initiated the field called **logic**.

Syllogisms

Logicians in the 19th century developed a precise notation for statements about objects in the world and the relations among them. (Contrast this with ordinary arithmetic notation, which provides only for statements about *numbers*.) By 1965, programs could, in principle, solve *any* solvable problem described in logical notation. The so-called **logicist** tradition within artificial intelligence hopes to build on such programs to create intelligent systems.

Logicist

Logic as conventionally understood requires knowledge of the world that is *certain*—a condition that, in reality, is seldom achieved. We simply don't know the rules of, say,

politics or warfare in the same way that we know the rules of chess or arithmetic. The theory of **probability** fills this gap, allowing rigorous reasoning with uncertain information. In principle, it allows the construction of a comprehensive model of rational thought, leading from raw perceptual information to an understanding of how the world works to predictions about the future. What it does not do, is generate intelligent *behavior*. For that, we need a theory of rational action. Rational thought, by itself, is not enough.

Probability

1.1.4 Acting rationally: The rational agent approach

Agent

An **agent** is just something that acts (*agent* comes from the Latin *agere*, to do). Of course, all computer programs do something, but computer agents are expected to do more: operate autonomously, perceive their environment, persist over a prolonged time period, adapt to change, and create and pursue goals. A **rational agent** is one that acts so as to achieve the best outcome or, when there is uncertainty, the best expected outcome.

Rational agent

In the "laws of thought" approach to AI, the emphasis was on correct inferences. Making correct inferences is sometimes *part* of being a rational agent, because one way to act rationally is to deduce that a given action is best and then to act on that conclusion. On the other hand, there are ways of acting rationally that cannot be said to involve inference. For

example, recoiling from a hot stove is a reflex action that is usually more successful than a slower action taken after careful deliberation.

All the skills needed for the Turing test also allow an agent to act rationally. Knowledge representation and reasoning enable agents to reach good decisions. We need to be able to generate comprehensible sentences in natural language to get by in a complex society. We need learning not only for erudition, but also because it improves our ability to generate effective behavior, especially in circumstances that are new.

The rational-agent approach to AI has two advantages over the other approaches. First, it is more general than the "laws of thought" approach because correct inference is just one of several possible mechanisms for achieving rationality. Second, it is more amenable to scientific development. The standard of rationality is mathematically well defined and completely general. We can often work back from this specification to derive agent designs that provably achieve it—something that is largely impossible if the goal is to imitate human behavior or thought processes.

For these reasons, the rational-agent approach to AI has prevailed throughout most of the field's history. In the early decades, rational agents were built on logical foundations and formed definite plans to achieve specific goals. Later, methods based on probability theory and machine learning allowed the creation of agents that could make decisions under uncertainty to attain the best expected outcome. In a nutshell, *AI has focused on the study and construction of agents that* ***do the right thing***. What counts as the right thing is defined by the objective that we provide to the agent. This general paradigm is so pervasive that we might call it the **standard model**. It prevails not only in AI, but also in control theory, where a controller minimizes a cost function; in operations research, where a policy maximizes a sum of rewards; in statistics, where a decision rule minimizes a loss function; and in economics, where a decision maker maximizes utility or some measure of social welfare.

Do the right thing

Standard model

We need to make one important refinement to the standard model to account for the fact that perfect rationality—always taking the exactly optimal action—is not feasible in complex environments. The computational demands are just too high. Chapters 5 and 17 deal with the issue of **limited rationality**—acting appropriately when there is not enough time to do all the computations one might like. However, perfect rationality often remains a good starting point for theoretical analysis.

Limited rationality

1.1.5 Beneficial machines

The standard model has been a useful guide for AI research since its inception, but it is probably not the right model in the long run. The reason is that the standard model assumes that we will supply a fully specified objective to the machine.

For an artificially defined task such as chess or shortest-path computation, the task comes with an objective built in—so the standard model is applicable. As we move into the real world, however, it becomes more and more difficult to specify the objective completely and correctly. For example, in designing a self-driving car, one might think that the objective is to reach the destination safely. But driving along any road incurs a risk of injury due to other errant drivers, equipment failure, and so on; thus, a strict goal of safety requires staying in the garage. There is a tradeoff between making progress towards the destination and incurring a risk of injury. How should this tradeoff be made? Furthermore, to what extent can we allow the car to take actions that would annoy other drivers? How much should the car moderate its acceleration, steering, and braking to avoid shaking up the passenger? These kinds of questions are difficult to answer a priori. They are particularly problematic in the general area of human–robot interaction, of which the self-driving car is one example.

The problem of achieving agreement between our true preferences and the objective we put into the machine is called the **value alignment problem**: the values or objectives put into

the machine must be aligned with those of the human. If we are developing an AI system in the lab or in a simulator—as has been the case for most of the field's history—there is an easy fix for an incorrectly specified objective: reset the system, fix the objective, and try again. As the field progresses towards increasingly capable intelligent systems that are deployed in the real world, this approach is no longer viable. A system deployed with an incorrect objective will have negative consequences. Moreover, the more intelligent the system, the more negative the consequences.

Value alignment problem

Returning to the apparently unproblematic example of chess, consider what happens if the machine is intelligent enough to reason and act beyond the confines of the chessboard. In that case, it might attempt to increase its chances of winning by such ruses as hypnotizing or blackmailing its opponent or bribing the audience to make rustling noises during its opponent's thinking time.[3] It might also attempt to hijack additional computing power for itself. *These behaviors are not "unintelligent" or "insane"; they are a logical consequence of defining winning as the sole objective for the machine.*

3 In one of the first books on chess, Ruy Lopez (1561) wrote, "Always place the board so the sun is in your opponent's eyes."

It is impossible to anticipate all the ways in which a machine pursuing a fixed objective might misbehave. There is good reason, then, to think that the standard model is inadequate. We don't want machines that are intelligent in the sense of pursuing *their* objectives; we want them to pursue *our* objectives. If we cannot transfer those objectives perfectly to the machine, then we need a new formulation—one in which the machine is pursuing our objectives, but is necessarily *uncertain* as to what they are. When a machine knows that it doesn't know the complete objective, it has an incentive to act cautiously, to ask permission, to learn more about our preferences through observation, and to defer to human control. Ultimately, we want agents that are **provably beneficial** to humans. We will return to this topic in Section 1.5.

1.2 The Foundations of Artificial Intelligence

In this section, we provide a brief history of the disciplines that contributed ideas, viewpoints, and techniques to AI. Like any history, this one concentrates on a small number of people, events, and ideas and ignores others that also were important. We organize the history around a series of questions. We certainly would not wish to give the impression that these questions are the only ones the disciplines address or that the disciplines have all been working toward AI as their ultimate fruition.

1.2.1 Philosophy

- Can formal rules be used to draw valid conclusions?
- How does the mind arise from a physical brain?
- Where does knowledge come from?
- How does knowledge lead to action?

Aristotle (384–322 BCE) was the first to formulate a precise set of laws governing the rational part of the mind. He developed an informal system of syllogisms for proper reasoning, which in principle allowed one to generate conclusions mechanically, given initial premises.

Ramon Llull (c. 1232–1315) devised a system of reasoning published as *Ars Magna* or *The Great Art* (1305). Llull tried to implement his system using an actual mechanical device: a set of paper wheels that could be rotated into different permutations.

Around 1500, Leonardo da Vinci (1452–1519) designed but did not build a mechanical calculator; recent reconstructions have shown the design to be functional. The first known calculating machine was constructed around 1623 by the German scientist Wilhelm Schickard (1592–1635). Blaise Pascal (1623–1662) built the Pascaline in 1642 and wrote that it "produces effects which appear nearer to thought than all the actions of animals." Gottfried Wilhelm Leibniz (1646–1716) built a mechanical device intended to carry out operations on concepts rather than numbers, but its scope was rather limited. In his 1651 book *Leviathan*, Thomas Hobbes (1588–1679) suggested the idea of a thinking machine, an "artificial animal" in his words, arguing "For what is the heart but a spring; and the nerves, but so many strings; and the joints, but so many wheels." He also suggested that reasoning

was like numerical computation: "For 'reason' ... is nothing but 'reckoning,' that is adding and subtracting."

It's one thing to say that the mind operates, at least in part, according to logical or numerical rules, and to build physical systems that emulate some of those rules. It's another to say that the mind itself *is* such a physical system. René Descartes (1596–1650) gave the first clear discussion of the distinction between mind and matter. He noted that a purely physical conception of the mind seems to leave little room for free will. If the mind is governed entirely by physical laws, then it has no more free will than a rock "deciding" to fall downward. Descartes was a proponent of **dualism**. He held that there is a part of the human mind (or soul or spirit) that is outside of nature, exempt from physical laws. Animals, on the other hand, did not possess this dual quality; they could be treated as machines.

Dualism

An alternative to dualism is **materialism**, which holds that the brain's operation according to the laws of physics *constitutes* the mind. Free will is simply the way that the perception of available choices appears to the choosing entity. The terms **physicalism** and **naturalism** are also used to describe this view that stands in contrast to the supernatural.

Given a physical mind that manipulates knowledge, the next problem is to establish the source of knowledge. The **empiricism** movement, starting with Francis Bacon's (1561–1626) *Novum Organum*,[4] is characterized by a dictum of John Locke (1632–1704): "Nothing is in the understanding, which was not first in the senses."

4 The *Novum Organum* is an update of Aristotle's *Organon*, or instrument of thought.

Empiricism

Induction

David Hume's (1711–1776) *A Treatise of Human Nature* (Hume, 1739) proposed what is now known as the principle of **induction**: that general rules are acquired by exposure to repeated associations between their elements.

Building on the work of Ludwig Wittgenstein (1889–1951) and Bertrand Russell (1872–1970), the famous Vienna Circle [2017], a group of philosophers and mathematicians meeting in Vienna in the 1920s and 1930s, developed the doctrine of **logical positivism**. This doctrine holds that all knowledge can be characterized by logical theories connected, ultimately, to **observation sentences** that correspond to sensory inputs; thus logical positivism combines rationalism and empiricism.

Logical positivism

Observation sentence

The **confirmation theory** of Rudolf Carnap (1891–1970) and Carl Hempel (1905–1997) attempted to analyze the acquisition of knowledge from experience by quantifying the degree of belief that should be assigned to logical sentences based on their connection to observations that confirm or disconfirm them. Carnap's book *The Logical Structure of the World* (1928) was perhaps the first theory of mind as a computational process.

Confirmation theory

The final element in the philosophical picture of the mind is the connection between knowledge and action. This question is vital to AI because intelligence requires action as well as reasoning. Moreover, only by understanding how actions are justified can we understand how to build an agent whose actions are justifiable (or rational).

Aristotle argued (in *De Motu Animalium*) that actions are justified by a logical connection between goals and knowledge of the action's outcome:

> But how does it happen that thinking is sometimes accompanied by action and sometimes not, sometimes by motion, and sometimes not? It looks as if almost the same thing happens as in the case of reasoning and making inferences about unchanging objects. But in that case the end is a speculative proposition … whereas here the conclusion which results from the two premises is an action. … I need covering; a cloak is a covering. I need a cloak. What I need, I have to make; I need a cloak. I have to make a cloak. And the conclusion, the "I have to make a cloak," is an action.

In the *Nicomachean Ethics* (Book III. 3, 1112b), Aristotle further elaborates on this topic, suggesting an algorithm:

> We deliberate not about ends, but about means. For a doctor does not deliberate whether he shall heal, nor an orator whether he shall persuade, … They assume the end and consider how and by what means it is attained, and if it seems easily and best produced thereby; while if it is achieved by one means only they consider *how* it will be achieved by this and by what means *this* will be achieved, till they come to the first cause, … and what is last in the order of analysis seems to be first in the order of becoming. And if we come on an impossibility, we give up the search, e.g., if we need money and this cannot be got; but if a thing appears possible we try to do it.

Aristotle's algorithm was implemented 2300 years later by Newell and Simon in their **General Problem Solver** program. We would now call it a greedy regression planning system (see Chapter 11). Methods based on logical planning to achieve definite goals dominated the first few decades of theoretical research in AI.

Utility

Thinking purely in terms of actions achieving goals is often useful but sometimes inapplicable. For example, if there are several different ways to achieve a goal, there needs to be some way to choose among them. More importantly, it may not be possible to achieve a goal with certainty, but some action must still be taken. How then should one decide? Antoine Arnauld (1662), analyzing the notion of rational decisions in gambling, proposed a quantitative formula for maximizing the expected monetary value of the outcome. Later, Daniel Bernoulli (1738) introduced the more general notion of **utility** to capture the internal, subjective value of an outcome. The modern notion of rational decision making under uncertainty involves maximizing expected utility, as explained in Chapter 16.

In matters of ethics and public policy, a decision maker must consider the interests of multiple individuals. Jeremy Bentham (1823) and John Stuart Mill (1863) promoted the idea of **utilitarianism**: that rational decision making based on maximizing utility should apply to all spheres of human activity, including public policy decisions made on behalf of many individuals. Utilitarianism is a specific kind of **consequentialism**: the idea that what is right and wrong is determined by the expected outcomes of an action.

Utilitarianism

In contrast, Immanuel Kant, in 1875 proposed a theory of rule-based or **deontological ethics**, in which "doing the right thing" is determined not by outcomes but by universal social laws that govern allowable actions, such as "don't lie" or "don't kill." Thus, a utilitarian could tell a white lie if the expected good outweighs the bad, but a Kantian would be bound not to, because lying is inherently wrong. Mill acknowledged the value of rules, but understood them as efficient decision procedures compiled from first-principles reasoning about consequences. Many modern AI systems adopt exactly this approach.

Deontological ethics

1.2.2 Mathematics

- What are the formal rules to draw valid conclusions?
- What can be computed?
- How do we reason with uncertain information?

Philosophers staked out some of the fundamental ideas of AI, but the leap to a formal science required the mathematization of logic and probability and the introduction of a new branch of mathematics: computation.

The idea of **formal logic** can be traced back to the philosophers of ancient Greece, India, and China, but its mathematical development really began with the work of George Boole (1815–1864), who worked out the details of propositional, or Boolean, logic (Boole, 1847). In 1879, Gottlob Frege (1848–1925) extended Boole's logic to include objects and relations, creating the first-order logic that is used today.[5] In addition to its central role in the early period of AI research, first-order logic motivated the work of Gödel and Turing that underpinned computation itself, as we explain below.

5 Frege's proposed notation for first-order logic—an arcane combination of textual and geometric features—never became popular.

Formal logic

The theory of **probability** can be seen as generalizing logic to situations with uncertain information—a consideration of great importance for AI. Gerolamo Cardano (1501–1576) first framed the idea of probability, describing it in terms of the possible outcomes of gambling events. In 1654, Blaise Pascal (1623–1662), in a letter to Pierre Fermat (1601–1665), showed how to predict the future of an unfinished gambling game and assign average payoffs to the gamblers. Probability quickly became an invaluable part of the quantitative sciences, helping to deal with uncertain measurements and incomplete theories. Jacob Bernoulli (1654–1705, uncle of Daniel), Pierre Laplace (1749–1827), and others advanced the theory and introduced new statistical methods. Thomas Bayes (1702–1761) proposed a rule for updating probabilities in the light of new evidence; Bayes' rule is a crucial tool for AI systems.

Probability

Statistics

The formalization of probability, combined with the availability of data, led to the emergence of **statistics** as a field. One of the first uses was John Graunt's analysis of London census data in 1662. Ronald Fisher is considered the first modern statistician (Fisher, 1922). He brought together the ideas of probability, experiment design, analysis of data, and computing—in 1919, he insisted that he couldn't do his work without a mechanical calculator called the MILLIONAIRE (the first calculator that could do multiplication), even though the cost of the calculator was more than his annual salary (Ross, 2012).

The history of computation is as old as the history of numbers, but the first nontrivial **algorithm** is thought to be Euclid's algorithm for computing greatest common divisors. The word *algorithm* comes from Muhammad ibn Musa al-Khwarizmi, a 9th century mathematician, whose writings also introduced Arabic numerals and algebra to Europe. Boole and others discussed algorithms for logical deduction, and, by the late 19th century, efforts were under way to formalize general mathematical reasoning as logical deduction.

Algorithm

Kurt Gödel (1906–1978) showed that there exists an effective procedure to prove any true statement in the first-order logic of Frege and Russell, but that first-order logic could not capture the principle of mathematical induction needed to characterize the natural numbers. In 1931, Gödel showed that limits on deduction do exist. His **incompleteness theorem** showed that in any formal theory as strong as Peano arithmetic (the elementary theory of natural numbers), there are necessarily true statements that have no proof within the theory.

Incompleteness theorem

This fundamental result can also be interpreted as showing that some functions on the integers cannot be represented by an algorithm—that is, they cannot be computed. This motivated Alan Turing (1912–1954) to try to characterize exactly which functions *are* **computable**—capable of being computed by an effective procedure. The Church–Turing thesis proposes to identify the general notion of computability with functions computed by a Turing machine (Turing, 1936). Turing also showed that there were some functions that no Turing machine can compute. For example, no machine can tell *in general* whether a given program will return an answer on a given input or run forever.

Computability

Although computability is important to an understanding of computation, the notion of **tractability** has had an even greater impact on AI. Roughly speaking, a problem is called intractable if the time required to solve instances of the problem grows exponentially with the size of the instances. The distinction between polynomial and exponential growth in complexity was first emphasized in the mid-1960s (Cobham, 1964; Edmonds, 1965). It is important because exponential growth means that even moderately large instances cannot be solved in any reasonable time.

Tractability

The theory of **NP-completeness**, pioneered by Cook (1971) and Karp (1972), provides a basis for analyzing the tractability of problems: any problem class to which the class of NP-complete problems can be reduced is likely to be intractable. (Although it has not been proved that NP-complete problems are necessarily intractable, most theoreticians believe

it.) These results contrast with the optimism with which the popular press greeted the first computers—"Electronic Super-Brains" that were "Faster than Einstein!" Despite the increasing speed of computers, careful use of resources and necessary imperfection will characterize intelligent systems. Put crudely, the world is an *extremely* large problem instance!

NP-completeness

1.2.3 Economics

- How should we make decisions in accordance with our preferences?
- How should we do this when others may not go along?
- How should we do this when the payoff may be far in the future?

The science of economics originated in 1776, when Adam Smith (1723–1790) published *An Inquiry into the Nature and Causes of the Wealth of Nations*. Smith proposed to analyze economies as consisting of many individual agents attending to their own interests. Smith was not, however, advocating financial greed as a moral position: his earlier (1759) book *The Theory of Moral Sentiments* begins by pointing out that concern for the well-being of others is an essential component of the interests of every individual.

Most people think of economics as being about money, and indeed the first mathematical analysis of decisions under uncertainty, the maximum-expected-value formula of Arnauld (1662), dealt with the monetary value of bets. Daniel Bernoulli (1738) noticed that this formula didn't seem to work well for larger amounts of money, such as investments in maritime trading expeditions. He proposed instead a principle based on maximization of expected utility, and explained human investment choices by proposing that the marginal utility of an additional quantity of money diminished as one acquired more money.

Léon Walras (pronounced "Valrasse") (1834–1910) gave utility theory a more general foundation in terms of preferences between gambles on any outcomes (not just monetary outcomes). The theory was improved by Ramsey (1931) and later by John von Neumann

and Oskar Morgenstern in their book *The Theory of Games and Economic Behavior* (1944). Economics is no longer the study of money; rather it is the study of desires and preferences.

Decision theory, which combines probability theory with utility theory, provides a formal and complete framework for individual decisions (economic or otherwise) made under uncertainty—that is, in cases where probabilistic descriptions appropriately capture the decision maker's environment. This is suitable for "large" economies where each agent need pay no attention to the actions of other agents as individuals. For "small" economies, the situation is much more like a **game**: the actions of one player can significantly affect the utility of another (either positively or negatively). Von Neumann and Morgenstern's development of **game theory** (see also Luce and Raiffa, 1957) included the surprising result that, for some games, a rational agent should adopt policies that are (or least appear to be) randomized. Unlike decision theory, game theory does not offer an unambiguous prescription for selecting actions. In AI, decisions involving multiple agents are studied under the heading of **multiagent systems** (Chapter 18).

Decision theory

Economists, with some exceptions, did not address the third question listed above: how to make rational decisions when payoffs from actions are not immediate but instead result from several actions taken *in sequence*. This topic was pursued in the field of **operations research**, which emerged in World War II from efforts in Britain to optimize radar installations, and later found innumerable civilian applications. The work of Richard Bellman (1957) formalized a class of sequential decision problems called **Markov decision processes**, which we study in Chapter 17 and, under the heading of **reinforcement learning**, in Chapter 22.

Operations research

Work in economics and operations research has contributed much to our notion of rational agents, yet for many years AI research developed along entirely separate paths. One reason was the apparent complexity of making rational decisions. The pioneering AI researcher Herbert Simon (1916–2001) won the Nobel Prize in economics in 1978 for his early work showing that models based on **satisficing**—making decisions that are "good enough," rather than laboriously calculating an optimal decision—gave a better description of actual human behavior (Simon, 1947). Since the 1990s, there has been a resurgence of interest in decision-theoretic techniques for AI.

Satisficing

1.2.4 Neuroscience

- How do brains process information?

Neuroscience is the study of the nervous system, particularly the brain. Although the exact way in which the brain enables thought is one of the great mysteries of science, the fact that it *does* enable thought has been appreciated for thousands of years because of the evidence that strong blows to the head can lead to mental incapacitation. It has also long been known that human brains are somehow different; in about 335 BCE Aristotle wrote, "Of all the animals, man has the largest brain in proportion to his size."[6] Still, it was not until the middle of the 18th century that the brain was widely recognized as the seat of consciousness. Before then, candidate locations included the heart and the spleen.

6 It has since been discovered that the tree shrew and some bird species exceed the human brain/body ratio.

Neuroscience

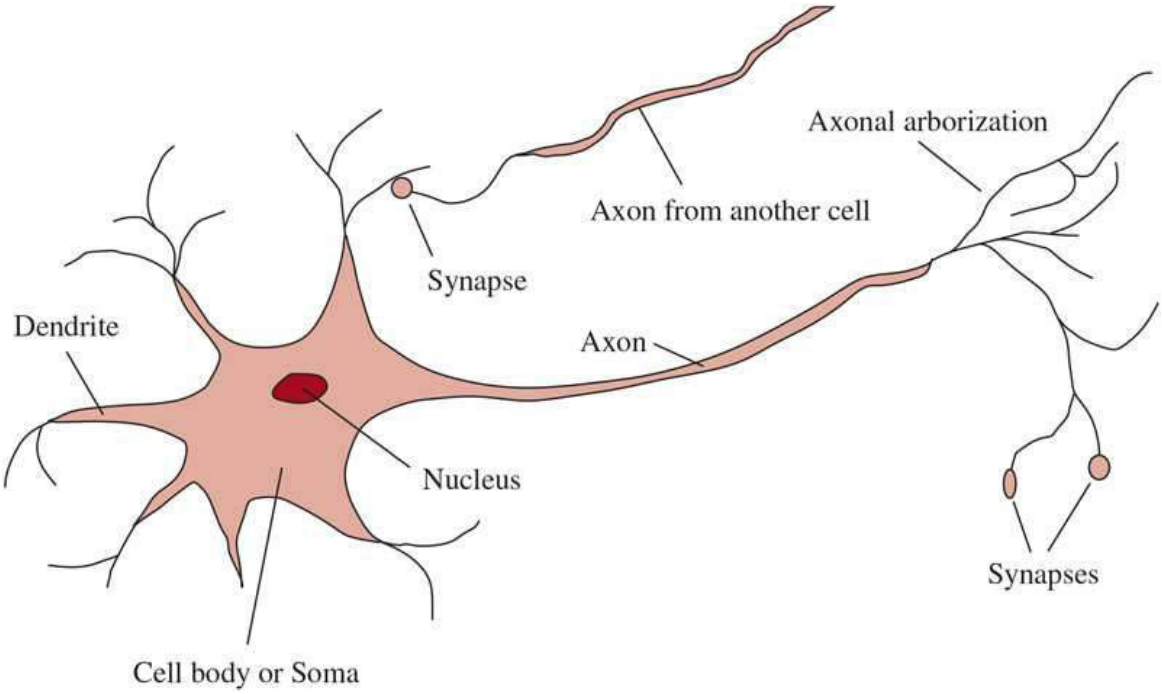
Paul Broca's (1824–1880) investigation of aphasia (speech deficit) in brain-damaged patients in 1861 initiated the study of the brain's functional organization by identifying a localized

area in the left hemisphere—now called Broca's area—that is responsible for speech production.[7] By that time, it was known that the brain consisted largely of nerve cells, or **neurons**, but it was not until 1873 that Camillo Golgi (1843–1926) developed a staining technique allowing the observation of individual neurons (see Figure 1.1). This technique was used by Santiago Ramon y Cajal (1852–1934) in his pioneering studies of neuronal organization.[8] It is now widely accepted that cognitive functions result from the electrochemical operation of these structures. That is, *a collection of simple cells can lead to thought, action, and consciousness.* In the pithy words of John Searle (1992), *brains cause minds*.

7 Many cite Alexander Hood (1824) as a possible prior source.

8 Golgi persisted in his belief that the brain's functions were carried out primarily in a continuous medium in which neurons were embedded, whereas Cajal propounded the "neuronal doctrine." The two shared the Nobel Prize in 1906 but gave mutually antagonistic acceptance speeches.

Figure 1.1



The parts of a nerve cell or neuron. Each neuron consists of a cell body, or soma, that contains a cell nucleus. Branching out from the cell body are a number of fibers called dendrites and a single long fiber called the axon. The axon stretches out for a long distance, much longer than the scale in this diagram indicates. Typically, an axon is 1 cm long (100 times the diameter of the cell body), but can reach up to 1 meter. A neuron makes connections with 10 to 100,000 other neurons at junctions called synapses. Signals are propagated from neuron to neuron by a complicated electrochemical reaction. The signals control brain activity in the short term and also enable long-term changes in the connectivity of neurons. These mechanisms are thought to form the basis for learning in the brain. Most information processing

goes on in the cerebral cortex, the outer layer of the brain. The basic organizational unit appears to be a column of tissue about 0.5 mm in diameter, containing about 20,000 neurons and extending the full depth of the cortex (about 4 mm in humans).

Neuron

We now have some data on the mapping between areas of the brain and the parts of the body that they control or from which they receive sensory input. Such mappings are able to change radically over the course of a few weeks, and some animals seem to have multiple maps. Moreover, we do not fully understand how other areas can take over functions when one area is damaged. There is almost no theory on how an individual memory is stored or on how higher-level cognitive functions operate.

The measurement of intact brain activity began in 1929 with the invention by Hans Berger of the electroencephalograph (EEG). The development of functional magnetic resonance imaging (fMRI) (Ogawa *et al.*, 1990; Cabeza and Nyberg, 2001) is giving neuroscientists unprecedentedly detailed images of brain activity, enabling measurements that correspond in interesting ways to ongoing cognitive processes. These are augmented by advances in single-cell electrical recording of neuron activity and by the methods of **optogenetics** (Crick, 1999; Optogenetics Zemelman *et al.*, 2002; Han and Boyden, 2007), which allow both measurement and control of individual neurons modified to be light-sensitive.

Optogenetics

The development of **brain–machine interfaces** (Lebedev and Nicolelis, 2006) for both sensing and motor control not only promises to restore function to disabled individuals, but also sheds light on many aspects of neural systems. A remarkable finding from this work is that the brain is able to adjust itself to interface successfully with an external device, treating it in effect like another sensory organ or limb.

Brain–machine interface

Brains and digital computers have somewhat different properties. Figure 1.2 shows that computers have a cycle time that is a million times faster than a brain. The brain makes up for that with far more storage and interconnection than even a high-end personal computer, although the largest supercomputers match the brain on some metrics. Futurists make much of these numbers, pointing to an approaching **singularity** at which computers reach a superhuman level of performance (Vinge, 1993; Kurzweil, 2005; Doctorow and Stross, 2012), and then rapidly improve themselves even further. But the comparisons of raw numbers are not especially informative. Even with a computer of virtually unlimited capacity, we still require further conceptual breakthroughs in our understanding of intelligence (see Chapter 28). Crudely put, without the right theory, faster machines just give you the wrong answer faster.

Singularity

Figure 1.2

	Supercomputer	Personal Computer	Human Brain
Computational units	10^6 GPUs + CPUs 10^{15} transistors	8 CPU cores 10^{10} transistors	10^6 columns 10^{11} neurons
Storage units	10^{16} bytes RAM 10^{17} bytes disk	10^{10} bytes RAM 10^{12} bytes disk	10^{11} neurons 10^{14} synapses
Cycle time	10^{-9} sec	10^{-9} sec	10^{-3} sec
Operations/sec	10^{18}	10^{10}	10^{17}

A crude comparison of a leading supercomputer, Summit (Feldman, 2017); a typical personal computer of 2019; and the human brain. Human brain power has not changed much in thousands of years, whereas supercomputers have improved from megaFLOPs in the 1960s to gigaFLOPs in the 1980s, teraFLOPs in the 1990s, petaFLOPs in 2008, and exaFLOPs in 2018 (1 exaFLOP $= 10^{18}$ floating point operations per second).

1.2.5 Psychology

- How do humans and animals think and act?

The origins of scientific psychology are usually traced to the work of the German physicist Hermann von Helmholtz (1821–1894) and his student Wilhelm Wundt (1832–1920). Helmholtz applied the scientific method to the study of human vision, and his *Handbook of Physiological Optics* has been described as "the single most important treatise on the physics and physiology of human vision" (Nalwa, 1993, p.15). In 1879, Wundt opened the first laboratory of experimental psychology, at the University of Leipzig. Wundt insisted on carefully controlled experiments in which his workers would perform a perceptual or associative task while introspecting on their thought processes. The careful controls went a long way toward making psychology a science, but the subjective nature of the data made it unlikely that experimenters would ever disconfirm their own theories.

Biologists studying animal behavior, on the other hand, lacked introspective data and developed an objective methodology, as described byH. S. Jennings (1906) in his influential work *Behavior of the Lower Organisms*. Applying this viewpoint to humans, the **behaviorism** movement, led by John Watson (1878–1958), rejected *any* theory involving mental processes on the grounds that introspection could not provide reliable evidence. Behaviorists insisted on studying only objective measures of the percepts (or *stimulus*) given to an animal and its resulting actions (or *response*). Behaviorism discovered a lot about rats and pigeons but had less success at understanding humans.

Behaviorism

Cognitive psychology, which views the brain as an information-processing device, can be traced back at least to the works of William James (1842–1910). Helmholtz also insisted that perception involved a form of unconscious logical inference. The cognitive viewpoint was largely eclipsed by behaviorism in the United States, but at Cambridge's Applied Psychology Unit, directed by Frederic Bartlett (1886–1969), cognitive modeling was able to flourish. *The Nature of Explanation*, by Bartlett's student and successor Kenneth Craik (1943), forcefully reestablished the legitimacy of such "mental" terms as beliefs and goals, arguing that they

are just as scientific as, say, using pressure and temperature to talk about gases, despite gasses being made of molecules that have neither.

Cognitive psychology

Craik specified the three key steps of a knowledge-based agent: (1) the stimulus must be translated into an internal representation, (2) the representation is manipulated by cognitive processes to derive new internal representations, and (3) these are in turn retranslated back into action. He clearly explained why this was a good design for an agent:

> If the organism carries a "small-scale model" of external reality and of its own possible actions within its head, it is able to try out various alternatives, conclude which is the best of them, react to future situations before they arise, utilize the knowledge of past events in dealing with the present and future, and in every way to react in a much fuller, safer, and more competent manner to the emergencies which face it. (Craik, 1943)

After Craik's death in a bicycle accident in 1945, his work was continued by Donald Broadbent, whose book *Perception and Communication* (1958) was one of the first works to model psychological phenomena as information processing. Meanwhile, in the United States, the development of computer modeling led to the creation of the field of **cognitive science**. The field can be said to have started at a workshop in September 1956 at MIT—just two months after the conference at which AI itself was "born."

At the workshop, George Miller presented *The Magic Number Seven*, Noam Chomsky presented *Three Models of Language*, and Allen Newell and Herbert Simon presented *The Logic Theory Machine*. These three influential papers showed how computer models could be used to address the psychology of memory, language, and logical thinking, respectively. It is now a common (although far from universal) view among psychologists that "a cognitive theory should be like a computer program" (Anderson, 1980); that is, it should describe the operation of a cognitive function in terms of the processing of information.

For purposes of this review, we will count the field of **human–computer interaction** (HCI) under psychology. Doug Engelbart, one of the pioneers of HCI, championed the idea of **intelligence augmentation**—IA rather than AI. He believed that computers should augment human abilities rather than automate away human tasks. In 1968, Engelbart's "mother of all demos" showed off for the first time the computer mouse, a windowing system, hypertext, and video conferencing—all in an effort to demonstrate what human knowledge workers could collectively accomplish with some intelligence augmentation.

Intelligence augmentation

Today we are more likely to see IA and AI as two sides of the same coin, with the former emphasizing human control and the latter emphasizing intelligent behavior on the part of the machine. Both are needed for machines to be useful to humans.

1.2.6 Computer engineering

- How can we build an efficient computer?

The modern digital electronic computer was invented independently and almost simultaneously by scientists in three countries embattled in World War II. The first *operational* computer was the electromechanical Heath Robinson,[9] built in 1943 by Alan Turing's team for a single purpose: deciphering German messages. In 1943, the same group developed the Colossus, a powerful general-purpose machine based on vacuum tubes.[10] The first operational *programmable* computer was the Z-3, the invention of Konrad Zuse in Germany in 1941. Zuse also invented floating-point numbers and the first high-level programming language, Plankalkül. The first *electronic* computer, the ABC, was assembled by John Atanasoff and his student Clifford Berry between 1940 and 1942 at Iowa State University. Atanasoff's research received little support or recognition; it was the ENIAC, developed as part of a secret military project at the University of Pennsylvania by a team including John Mauchly and J. Presper Eckert, that proved to be the most influential forerunner of modern computers.

9 A complex machine named after a British cartoonist who depicted whimsical and absurdly complicated contraptions for everyday tasks such as buttering toast.

10 In the postwar period, Turing wanted to use these computers for AI research—for example, he created an outline of the first chess program (Turing et al., 1953) —but the British government blocked this research.

Moore's law

Since that time, each generation of computer hardware has brought an increase in speed and capacity and a decrease in price—a trend captured in **Moore's law**. Performance doubled every 18 months or so until around 2005, when power dissipation problems led manufacturers to start multiplying the number of CPU cores rather than the clock speed. Current expectations are that future increases in functionality will come from massive parallelism—a curious convergence with the properties of the brain. We also see new hardware designs based on the idea that in dealing with an uncertain world, we don't need 64 bits of precision in our numbers; just 16 bits (as in the bfloat16 format) or even 8 bits will be enough, and will enable faster processing.

We are just beginning to see hardware tuned for AI applications, such as the graphics processing unit (GPU), tensor processing unit (TPU), and wafer scale engine (WSE). From the 1960s to about 2012, the amount of computing power used to train top machine learning applications followed Moore's law. Beginning in 2012, things changed: from 2012 to 2018 there was a 300,000-fold increase, which works out to a doubling every 100 days or so (Amodei and Hernandez, 2018). A machine learning model that took a full day to train in 2014 takes only two minutes in 2018 (Ying *et al.*, 2018). Although it is not yet practical, **quantum computing** holds out the promise of far greater accelerations for some important subclasses of AI algorithms.

Quantum computing

Of course, there were calculating devices before the electronic computer. The earliest automated machines, dating from the 17th century, were discussed on 6. The first *programmable* machine was a loom, devised in 1805 by Joseph Marie Jacquard (1752–1834), that used punched cards to store instructions for the pattern to be woven.

In the mid-19th century, Charles Babbage (1792–1871) designed two computing machines, neither of which he completed. The Difference Engine was intended to compute mathematical tables for engineering and scientific projects. It was finally built and shown to work in 1991 (Swade, 2000). Babbage's Analytical Engine was far more ambitious: it included addressable memory, stored programs based on Jacquard's punched cards, and conditional jumps. It was the first machine capable of universal computation.

Babbage's colleague Ada Lovelace, daughter of the poet Lord Byron, understood its potential, describing it as "a thinking or ... a reasoning machine," one capable of reasoning about "all subjects in the universe" (Lovelace, 1843). She also anticipated AI's hype cycles, writing, "It is desirable to guard against the possibility of exaggerated ideas that might arise as to the powers of the Analytical Engine." Unfortunately, Babbage's machines and Lovelace's ideas were largely forgotten.

AI also owes a debt to the software side of computer science, which has supplied the operating systems, programming languages, and tools needed to write modern programs (and papers about them). But this is one area where the debt has been repaid: work in AI has pioneered many ideas that have made their way back to mainstream computer science, including time sharing, interactive interpreters, personal computers with windows and mice, rapid development environments, the linked-list data type, automatic storage management, and key concepts of symbolic, functional, declarative, and object-oriented programming.

1.2.7 Control theory and cybernetics

- How can artifacts operate under their own control?

Ktesibios of Alexandria (c. 250 BCE) built the first self-controlling machine: a water clock with a regulator that maintained a constant flow rate. This invention changed the definition of what an artifact could do. Previously, only living things could modify their behavior in response to changes in the environment. Other examples of self-regulating feedback control systems include the steam engine governor, created by James Watt (1736–1819), and the

thermostat, invented by Cornelis Drebbel (1572–1633), who also invented the submarine. James Clerk Maxwell (1868) initiated the mathematical theory of control systems.

A central figure in the post-war development of **control theory** was Norbert Wiener (1894–1964). Wiener was a brilliant mathematician who worked with Bertrand Russell, among others, before developing an interest in biological and mechanical control systems and their connection to cognition. Like Craik (who also used control systems as psychological models), Wiener and his colleagues Arturo Rosenblueth and Julian Bigelow challenged the behaviorist orthodoxy (Rosenblueth *et al.*, 1943). They viewed purposive behavior as arising from a regulatory mechanism trying to minimize "error"—the difference between current state and goal state. In the late 1940s, Wiener, along with Warren McCulloch, Walter Pitts, and John von Neumann, organized a series of influential conferences that explored the new mathematical and computational models of cognition. Wiener's book *Cybernetics* (1948) became a bestseller and awoke the public to the possibility of artificially intelligent machines.

Control theory

Cybernetics

Meanwhile, in Britain, W. Ross Ashby pioneered similar ideas (Ashby, 1940). Ashby, Alan Turing, Grey Walter, and others formed the Ratio Club for "those who had Wiener's ideas before Wiener's book appeared." Ashby's *Design for a Brain* 1948, 1952 elaborated on his idea that intelligence could be created by the use of **homeostatic** devices containing appropriate feedback loops to achieve stable adaptive behavior.

Homeostatic

Modern control theory, especially the branch known as stochastic optimal control, has as its goal the design of systems that maximize a **cost function** over time. This roughly matches the standard model of AI: designing systems that behave optimally. Why, then, are AI and control theory two different fields, despite the close connections among their founders? The answer lies in the close coupling between the mathematical techniques that were familiar to the participants and the corresponding sets of problems that were encompassed in each world view. Calculus and matrix algebra, the tools of control theory, lend themselves to systems that are describable by fixed sets of continuous variables, whereas AI was founded in part as a way to escape from these perceived limitations. The tools of logical inference and computation allowed AI researchers to consider problems such as language, vision, and symbolic planning that fell completely outside the control theorist's purview.

Cost function

1.2.8 Linguistics

- How does language relate to thought?

In 1957, B. F. Skinner published *Verbal Behavior*. This was a comprehensive, detailed account of the behaviorist approach to language learning, written by the foremost expert in the field. But curiously, a review of the book became as well known as the book itself, and served to almost kill off interest in behaviorism. The author of the review was the linguist Noam Chomsky, who had just published a book on his own theory, *Syntactic Structures*. Chomsky pointed out that the behaviorist theory did not address the notion of creativity in language—it did not explain how children could understand and make up sentences that they had never heard before. Chomsky's theory—based on syntactic models going back to the Indian linguist Panini (c. 350 BCE)—could explain this, and unlike previous theories, it was formal enough that it could in principle be programmed.

Computational linguistics

Modern linguistics and AI, then, were "born" at about the same time, and grew up together, intersecting in a hybrid field called **computational linguistics** or **natural language processing**. The problem of understanding language turned out to be considerably more complex than it seemed in 1957. Understanding language requires an understanding of the subject matter and context, not just an understanding of the structure of sentences. This might seem obvious, but it was not widely appreciated until the 1960s. Much of the early work in **knowledge representation** (the study of how to put knowledge into a form that a computer can reason with) was tied to language and informed by research in linguistics, which was connected in turn to decades of work on the philosophical analysis of language.

1.3 The History of Artificial Intelligence

One quick way to summarize the milestones in AI history is to list the Turing Award winners: Marvin Minsky (1969) and John McCarthy (1971) for defining the foundations of the field based on representation and reasoning; Ed Feigenbaum and Raj Reddy (1994) for developing expert systems that encode human knowledge to solve real-world problems; Judea Pearl (2011) for developing probabilistic reasoning techniques that deal with uncertainty in a principled manner; and finally Yoshua Bengio, Geoffrey Hinton, and Yann LeCun (2019) for making "deep learning" (multilayer neural networks) a critical part of modern computing. The rest of this section goes into more detail on each phase of AI history.

1.3.1 The inception of artificial intelligence (1943–1956)

The first work that is now generally recognized as AI was done by Warren McCulloch and Walter Pitts (1943). Inspired by the mathematical modeling work of Pitts's advisor Nicolas (1936, 1938), they drew on three sources: knowledge of the basic physiology and function of neurons in the brain; a formal analysis of propositional logic due to Russell and Whitehead; and Turing's theory of computation. They proposed a model of artificial neurons in which each neuron is characterized as being "on" or "off," with a switch to "on" occurring in response to stimulation by a sufficient number of neighboring neurons. The state of a neuron was conceived of as "factually equivalent to a proposition which proposed its adequate stimulus." They showed, for example, that any computable function could be computed by some network of connected neurons, and that all the logical connectives (AND, OR, NOT, etc.) could be implemented by simple network structures. McCulloch and Pitts also suggested that suitably defined networks could learn. Donald Hebb (1949) demonstrated a simple updating rule for modifying the connection strengths between neurons. His rule, now called **Hebbian learning**, remains an influential model to this day.

Hebbian learning

Two undergraduate students at Harvard, Marvin Minsky (1927–2016) and Dean Edmonds, built the first neural network computer in 1950. The SNARC, as it was called, used 3000 vacuum tubes and a surplus automatic pilot mechanism from a B-24 bomber to simulate a network of 40 neurons. Later, at Princeton, Minsky studied universal computation in neural networks. His Ph.D. committee was skeptical about whether this kind of work should be considered mathematics, but von Neumann reportedly said, "If it isn't now, it will be someday."

There were a number of other examples of early work that can be characterized as AI, including two checkers-playing programs developed independently in 1952 by Christopher Strachey at the University of Manchester and by Arthur Samuel at IBM. However, Alan Turing's vision was the most influential. He gave lectures on the topic as early as 1947 at the London Mathematical Society and articulated a persuasive agenda in his 1950 article "Computing Machinery and Intelligence." Therein, he introduced the Turing test, machine learning, genetic algorithms, and reinforcement learning. He dealt with many of the objections raised to the possibility of AI, as described in Chapter 27. He also suggested that it would be easier to create human-level AI by developing learning algorithms and then teaching the machine rather than by programming its intelligence by hand. In subsequent lectures he warned that achieving this goal might not be the best thing for the human race.

In 1955, John McCarthy of Dartmouth College convinced Minsky, Claude Shannon, and Nathaniel Rochester to help him bring together U.S. researchers interested in automata theory, neural nets, and the study of intelligence. They organized a two-month workshop at Dartmouth in the summer of 1956. There were 10 attendees in all, including Allen Newell and Herbert Simon from Carnegie Tech,[11] Trenchard More from Princeton, Arthur Samuel from IBM, and Ray Solomonoff and Oliver Selfridge from MIT. The proposal states:[12]

11 Now Carnegie Mellon University (CMU).

12 This was the first official usage of McCarthy's term *artificial intelligence*. Perhaps "computational rationality" would have been more precise and less threatening, but "AI" has stuck. At the 50th anniversary of the Dartmouth conference, McCarthy stated that he resisted the terms "computer" or "computational" in deference to Norbert Wiener, who was promoting analog cybernetic devices rather than digital computers.

> We propose that a 2 month, 10 man study of artificial intelligence be carried out during the summer of 1956 at Dartmouth College in Hanover, New Hampshire. The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so

> precisely described that a machine can be made to simulate it. An attempt will be made to find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves. We think that a significant advance can be made in one or more of these problems if a carefully selected group of scientists work on it together for a summer.

Despite this optimistic prediction, the Dartmouth workshop did not lead to any breakthroughs. Newell and Simon presented perhaps the most mature work, a mathematical theorem-proving system called the Logic Theorist (LT). Simon claimed, "We have invented a computer program capable of thinking non-numerically, and thereby solved the venerable mind–body problem."[13] Soon after the workshop, the program was able to prove most of the theorems in Chapter 2 of Russell and Whitehead's *Principia Mathematica*. Russell was reportedly delighted when told that LT had come up with a proof for one theorem that was shorter than the one in *Principia*. The editors of the *Journal of Symbolic Logic* were less impressed; they rejected a paper coauthored by Newell, Simon, and Logic Theorist.

13 Newell and Simon also invented a list-processing language, IPL, to write LT. They had no compiler and translated it into machine code by hand. To avoid errors, they worked in parallel, calling out binary numbers to each other as they wrote each instruction to make sure they agreed.

1.3.2 Early enthusiasm, great expectations (1952–1969)

The intellectual establishment of the 1950s, by and large, preferred to believe that "a machine can never do X." (See Chapter 27 for a long list of X's gathered by Turing.) AI researchers naturally responded by demonstrating one X after another. They focused in particular on tasks considered indicative of intelligence in humans, including games, puzzles, mathematics, and IQ tests. John McCarthy referred to this period as the "Look, Ma, no hands!" era.

Newell and Simon followed up their success with LT with the General Problem Solver, or GPS. Unlike LT, this program was designed from the start to imitate human problem-solving protocols. Within the limited class of puzzles it could handle, it turned out that the order in which the program considered subgoals and possible actions was similar to that in which humans approached the same problems. Thus, GPS was probably the first program to embody the "thinking humanly" approach. The success of GPS and subsequent programs as models of cognition led Newell and Simon (1976) to formulate the famous **physical symbol system** hypothesis, which states that "a physical symbol system has the necessary and

sufficient means for general intelligent action." What they meant is that any system (human or machine) exhibiting intelligence must operate by manipulating data structures composed of symbols. We will see later that this hypothesis has been challenged from many directions.

Physical symbol system

At IBM, Nathaniel Rochester and his colleagues produced some of the first AI programs. Herbert Gelernter (1959) constructed the Geometry Theorem Prover, which was able to prove theorems that many students of mathematics would find quite tricky. This work was a precursor of modern mathematical theorem provers.

Of all the exploratory work done during this period, perhaps the most influential in the long run was that of Arthur Samuel on checkers (draughts). Using methods that we now call reinforcement learning (see Chapter 22), Samuel's programs learned to play at a strong amateur level. He thereby disproved the idea that computers can do only what they are told to: his program quickly learned to play a better game than its creator. The program was demonstrated on television in 1956, creating a strong impression. Like Turing, Samuel had trouble finding computer time. Working at night, he used machines that were still on the testing floor at IBM's manufacturing plant. Samuel's program was the precursor of later systems such as TD-GAMMON (Tesauro, 1992), which was among the world's best backgammon players, and ALPHAGO (Silver *et al.*, 2016), which shocked the world by defeating the human world champion at Go (see Chapter 5).

In 1958, John McCarthy made two important contributions to AI. In MIT AI Lab Memo No. 1, he defined the high-level language **Lisp**, which was to become the dominant AI programming language for the next 30 years. In a paper entitled *Programs with Common Sense*, he advanced a conceptual proposal for AI systems based on knowledge and reasoning. The paper describes the Advice Taker, a hypothetical program that would embody general knowledge of the world and could use it to derive plans of action. The concept was illustrated with simple logical axioms that suffice to generate a plan to drive to the airport. The program was also designed to accept new axioms in the normal course of operation, thereby allowing it to achieve competence in new areas *without being*

reprogrammed. The Advice Taker thus embodied the central principles of knowledge representation and reasoning: that it is useful to have a formal, explicit representation of the world and its workings and to be able to manipulate that representation with deductive processes. The paper influenced the course of AI and remains relevant today.

Lisp

1958 also marked the year that Marvin Minsky moved to MIT. His initial collaboration with McCarthy did not last, however. McCarthy stressed representation and reasoning in formal logic, whereas Minsky was more interested in getting programs to work and eventually developed an anti-logic outlook. In 1963, McCarthy started the AI lab at Stanford. His plan to use logic to build the ultimate Advice Taker was advanced by J. A. Robinson's discovery in 1965 of the resolution method (a complete theorem-proving algorithm for first-order logic; see Chapter 9). Work at Stanford emphasized general-purpose methods for logical reasoning. Applications of logic included Cordell Green's question-answering and planning systems (Green, 1969b) and the Shakey robotics project at the Stanford Research Institute (SRI). The latter project, discussed further in Chapter 26, was the first to demonstrate the complete integration of logical reasoning and physical activity.

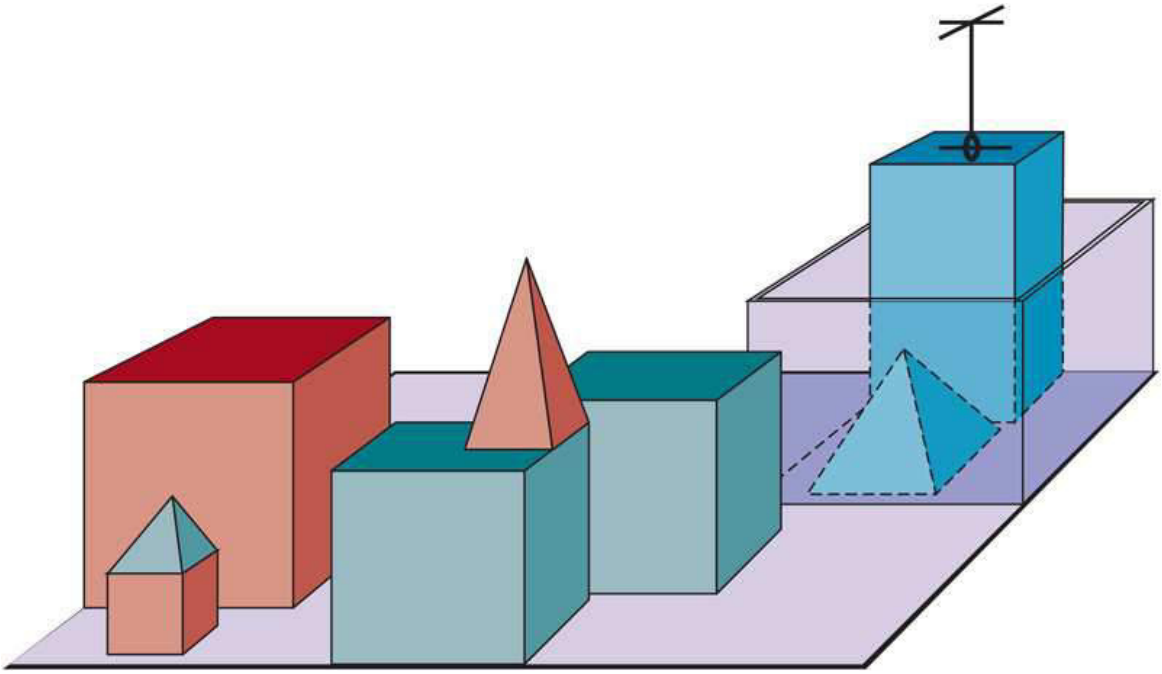
Microworld

At MIT, Minsky supervised a series of students who chose limited problems that appeared to require intelligence to solve. These limited domains became known as **microworlds**. James Slagle's SAINT program (1963) was able to solve closed-form calculus integration problems typical of first-year college courses. Tom Evans's ANALOGY program (1968) solved geometric analogy problems that appear in IQ tests. Daniel Bobrow's STUDENT program (1967) solved algebra story problems, such as the following:

> If the number of customers Tom gets is twice the square of 20 percent of the number of advertisements he runs, and the number of advertisements he runs is 45, what is the number of customers Tom gets?

The most famous microworld is the **blocks world**, which consists of a set of solid blocks placed on a tabletop (or more often, a simulation of a tabletop), as shown in Figure 1.3. A typical task in this world is to rearrange the blocks in a certain way, using a robot hand that can pick up one block at a time. The blocks world was home to the vision project of David Huffman (1971), the vision and constraint-propagation work of David Waltz (1975), the learning theory of Patrick Winston (1970), the natural-language-understanding program of Terry Winograd (1972), and the planner of Scott Fahlman (1974).

Figure 1.3



A scene from the blocks world. SHRDLU (Winograd, 1972) has just completed the command "Find a block which is taller than the one you are holding and put it in the box."

Blocks world

Early work building on the neural networks of McCulloch and Pitts also flourished. The work of Shmuel Winograd and Jack Cowan (1963) showed how a large number of elements could collectively represent an individual concept, with a corresponding increase in robustness and parallelism. Hebb's learning methods were enhanced by Bernie Widrow (Widrow and Hoff, 1960; Widrow, 1962), who called his networks **adalines**, and by Frank Rosenblatt (1962) with his **perceptrons**. The **perceptron convergence theorem** (Block *et al.*, 1962) says that the learning algorithm can adjust the connection strengths of a perceptron to match any input data, provided such a match exists.

1.3.3 A dose of reality (1966–1973)

From the beginning, AI researchers were not shy about making predictions of their coming successes. The following statement by Herbert Simon in 1957 is often quoted:

> It is not my aim to surprise or shock you—but the simplest way I can summarize is to say that there are now in the world machines that think, that learn and that create. Moreover, their ability to do these things is going to increase rapidly until—in a visible future—the range of problems they can handle will be coextensive with the range to which the human mind has been applied.

The term "visible future" is vague, but Simon also made more concrete predictions: that within 10 years a computer would be chess champion and a significant mathematical theorem would be proved by machine. These predictions came true (or approximately true) within 40 years rather than 10. Simon's overconfidence was due to the promising performance of early AI systems on simple examples. In almost all cases, however, these early systems failed on more difficult problems.

There were two main reasons for this failure. The first was that many early AI systems were based primarily on "informed introspection" as to how humans perform a task, rather than on a careful analysis of the task, what it means to be a solution, and what an algorithm would need to do to reliably produce such solutions.

The second reason for failure was a lack of appreciation of the intractability of many of the problems that AI was attempting to solve. Most of the early problem-solving systems worked by trying out different combinations of steps until the solution was found. This strategy worked initially because microworlds contained very few objects and hence very few possible actions and very short solution sequences. Before the theory of computational

complexity was developed, it was widely thought that "scaling up" to larger problems was simply a matter of faster hardware and larger memories. The optimism that accompanied the development of resolution theorem proving, for example, was soon dampened when researchers failed to prove theorems involving more than a few dozen facts. *The fact that a program can find a solution in principle does not mean that the program contains any of the mechanisms needed to find it in practice.*

The illusion of unlimited computational power was not confined to problem-solving programs. Early experiments in **machine evolution** (now called **genetic programming**) (Fried-Machine evolutionberg, 1958; Friedberg *et al.*, 1959) were based on the undoubtedly correct belief that by making an appropriate series of small mutations to a machine-code program, one can generate a program with good performance for any particular task. The idea, then, was to try random mutations with a selection process to preserve mutations that seemed useful. Despite thousands of hours of CPU time, almost no progress was demonstrated.

Machine evolution

Failure to come to grips with the "combinatorial explosion" was one of the main criticisms of AI contained in the Lighthill report (Lighthill, 1973), which formed the basis for the decision by the British government to end support for AI research in all but two universities. (Oral tradition paints a somewhat different and more colorful picture, with political ambitions and personal animosities whose description is beside the point.)

A third difficulty arose because of some fundamental limitations on the basic structures being used to generate intelligent behavior. For example, Minsky and Papert's book *Perceptrons* (1969) proved that, although perceptrons (a simple form of neural network) could be shown to learn anything they were capable of representing, they could represent very little. In particular, a two-input perceptron could not be trained to recognize when its two inputs were different. Although their results did not apply to more complex, multilayer networks, research funding for neural-net research soon dwindled to almost nothing. Ironically, the new back-propagation learning algorithms that were to cause an enormous

resurgence in neural-net research in the late 1980s and again in the 2010s had already been developed in other contexts in the early 1960s (Kelley, 1960; Bryson, 1962).

1.3.4 Expert systems (1969–1986)

The picture of problem solving that had arisen during the first decade of AI research was of a general-purpose search mechanism trying to string together elementary reasoning steps to find complete solutions. Such approaches have been called **weak methods** because, although general, they do not scale up to large or difficult problem instances. The alternative to weak methods is to use more powerful, domain-specific knowledge that allows larger reasoning steps and can more easily handle typically occurring cases in narrow areas of expertise. One might say that to solve a hard problem, you have to almost know the answer already.

Weak method

The DENDRAL program (Buchanan *et al.*, 1969) was an early example of this approach. It was developed at Stanford, where Ed Feigenbaum (a former student of Herbert Simon), Bruce Buchanan (a philosopher turned computer scientist), and Joshua Lederberg (a Nobel laureate geneticist) teamed up to solve the problem of inferring molecular structure from the information provided by a mass spectrometer. The input to the program consists of the elementary formula of the molecule (e.g., $C_6H_{13}NO_2$) and the mass spectrum giving the masses of the various fragments of the molecule generated when it is bombarded by an electron beam. For example, the mass spectrum might contain a peak at $m = 15$, corresponding to the mass of a methyl (CH_3) fragment.

The naive version of the program generated all possible structures consistent with the formula, and then predicted what mass spectrum would be observed for each, comparing this with the actual spectrum. As one might expect, this is intractable for even moderate-sized molecules. The DENDRAL researchers consulted analytical chemists and found that they worked by looking for well-known patterns of peaks in the spectrum that suggested common substructures in the molecule. For example, the following rule is used to recognize a ketone ($C{=}O$) subgroup (which weighs 28):

> **if** M is the mass of the whole molecule and there are two peaks at x_1 and x_2 such that (a) $x_1 + x_2 = M + 28$; (b) $x_1 - 28$ is a high peak; (c) $x_2 - 28$ is a high peak; and (d) At least one of x_1 and x_2 is high **then** there is a ketone subgroup.

Recognizing that the molecule contains a particular substructure reduces the number of possible candidates enormously. According to its authors, DENDRAL was powerful because it embodied the relevant knowledge of mass spectroscopy not in the form of first principles but in efficient "cookbook recipes" (Feigenbaum *et al.*, 1971). The significance of DENDRAL was that it was the first successful *knowledge-intensive* system: its expertise derived from large numbers of special-purpose rules. In 1971, Feigenbaum and others at Stanford began the Heuristic Programming Project (HPP) to investigate the extent to which the new methodology of **expert systems** could be applied to other areas.

Expert systems

The next major effort was the MYCIN system for diagnosing blood infections. With about 450 rules, MYCIN was able to perform as well as some experts, and considerably better than junior doctors. It also contained two major differences from DENDRAL. First, unlike the DENDRAL rules, no general theoretical model existed from which the MYCIN rules could be deduced. They had to be acquired from extensive interviewing of experts. Second, the rules had to reflect the uncertainty associated with medical knowledge. MYCIN incorporated a calculus of uncertainty called **certainty factors** (see Chapter 13), which seemed (at the time) to fit well with how doctors assessed the impact of evidence on the diagnosis.

Certainty factor

The first successful commercial expert system, R1, began operation at the Digital Equipment Corporation (McDermott, 1982). The program helped configure orders for new computer systems; by 1986, it was saving the company an estimated $40 million a year. By 1988,

DEC's AI group had 40 expert systems deployed, with more on the way. DuPont had 100 in use and 500 in development. Nearly every major U.S. corporation had its own AI group and was either using or investigating expert systems.

The importance of domain knowledge was also apparent in the area of natural language understanding. Despite the success of Winograd's SHRDLU system, its methods did not extend to more general tasks: for problems such as ambiguity resolution it used simple rules that relied on the tiny scope of the blocks world.

Several researchers, including Eugene Charniak at MIT and Roger Schank at Yale, suggested that robust language understanding would require general knowledge about the world and a general method for using that knowledge. (Schank went further, claiming, "There is no such thing as syntax," which upset a lot of linguists but did serve to start a useful discussion.) Schank and his students built a series of programs (Schank and Abelson, 1977; Wilensky, 1978; Schank and Riesbeck, 1981) that all had the task of understanding natural language. The emphasis, however, was less on language *per se* and more on the problems of representing and reasoning with the knowledge required for language understanding.

The widespread growth of applications to real-world problems led to the development of a wide range of representation and reasoning tools. Some were based on logic—for example, the Prolog language became popular in Europe and Japan, and the PLANNER family in the United States. Others, following Minsky's idea of **frames** (1975), adopted a more structured approach, assembling facts about particular object and event types and arranging the types into a large taxonomic hierarchy analogous to a biological taxonomy.

Frames

In 1981, the Japanese government announced the "Fifth Generation" project, a 10-year plan to build massively parallel, intelligent computers running Prolog. The budget was to exceed a $1.3 billion in today's money. In response, the United States formed the Microelectronics and Computer Technology Corporation (MCC), a consortium designed to assure national competitiveness. In both cases, AI was part of a broad effort, including chip design and

human-interface research. In Britain, the Alvey report reinstated the funding removed by the Lighthill report. However, none of these projects ever met its ambitious goals in terms of new AI capabilities or economic impact.

Overall, the AI industry boomed from a few million dollars in 1980 to billions of dollars in 1988, including hundreds of companies building expert systems, vision systems, robots, and software and hardware specialized for these purposes.

Soon after that came a period called the "AI winter," in which many companies fell by the wayside as they failed to deliver on extravagant promises. It turned out to be difficult to build and maintain expert systems for complex domains, in part because the reasoning methods used by the systems broke down in the face of uncertainty and in part because the systems could not learn from experience.

1.3.5 The return of neural networks (1986–present)

In the mid-1980s at least four different groups reinvented the **back-propagation** learning algorithm first developed in the early 1960s. The algorithm was applied to many learning problems in computer science and psychology, and the widespread dissemination of the results in the collection *Parallel Distributed Processing* (Rumelhart and McClelland, 1986) caused great excitement.

These so-called **connectionist** models were seen by some as direct competitors both to the symbolic models promoted by Newell and Simon and to the logicist approach of McCarthy and others. It might seem obvious that at some level humans manipulate symbols—in fact, the anthropologist Terrence Deacon's book *The Symbolic Species* (1997) suggests that this is the *defining characteristic* of humans. Against this, Geoff Hinton, a leading figure in the resurgence of neural networks in the 1980s and 2010s, has described symbols as the "luminiferous aether of AI"—a reference to the non-existent medium through which many 19th-century physicists believed that electromagnetic waves propagated. Certainly, many concepts that we name in language fail, on closer inspection, to have the kind of logically defined necessary and sufficient conditions that early AI researchers hoped to capture in axiomatic form. It may be that connectionist models form internal concepts in a more fluid and imprecise way that is better suited to the messiness of the real world. They also have the capability to learn from examples—they can compare their predicted output value to the

true value on a problem and modify their parameters to decrease the difference, making them more likely to perform well on future examples.

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connectionist

1.3.6 Probabilistic reasoning and machine learning (1987–present)

The brittleness of expert systems led to a new, more scientific approach incorporating probability rather than Boolean logic, machine learning rather than hand-coding, and experimental results rather than philosophical claims.[14] It became more common to build on existing theories than to propose brand-new ones, to base claims on rigorous theorems or solid experimental methodology (Cohen, 1995) rather than on intuition, and to show relevance to real-world applications rather than toy examples.

14 Some have characterized this change as a victory of the **neats**—those who think that AI theories should be grounded in mathematical rigor—over the **scruffies**—those who would rather try out lots of ideas, write some programs, and then assess what seems to be working. Both approaches are important. A shift toward neatness implies that the field has reached a level of stability and maturity. The present emphasis on deep learning may represent a resurgence of the scruffies.

Shared benchmark problem sets became the norm for demonstrating progress, including the UC Irvine repository for machine learning data sets, the International Planning Competition for planning algorithms, the LibriSpeech corpus for speech recognition, the MNIST data set for handwritten digit recognition, ImageNet and COCO for image object recognition, SQuAD for natural language question answering, the WMT competition for machine translation, and the International SAT Competitions for Boolean satisfiability solvers.

AI was founded in part as a rebellion against the limitations of existing fields like control theory and statistics, but in this period it embraced the positive results of those fields. As David McAllester (1998) put it:

> In the early period of AI it seemed plausible that new forms of symbolic computation, e.g., frames and semantic networks, made much of classical theory obsolete. This led to a form of isolationism in which AI became largely separated from the rest of computer science. This isolationism is currently

> being abandoned. There is a recognition that machine learning should not be isolated from information theory, that uncertain reasoning should not be isolated from stochastic modeling, that search should not be isolated from classical optimization and control, and that automated reasoning should not be isolated from formal methods and static analysis.

The field of speech recognition illustrates the pattern. In the 1970s, a wide variety of different architectures and approaches were tried. Many of these were rather ad hoc and fragile, and worked on only a few carefully selected examples. In the 1980s, approaches using **hidden Markov models** (HMMs) came to dominate the area. Two aspects of HMMs are relevant. First, they are based on a rigorous mathematical theory. This allowed speech researchers to build on several decades of mathematical results developed in other fields. Second, they are generated by a process of training on a large corpus of real speech data. This ensures that the performance is robust, and in rigorous blind tests HMMs improved their scores steadily. As a result, speech technology and the related field of handwritten character recognition made the transition to widespread industrial and consumer applications. Note that there was no scientific claim that humans use HMMs to recognize speech; rather, HMMs provided a mathematical framework for understanding and solving the problem. We will see in Section 1.3.8, however, that deep learning has rather upset this comfortable narrative.

Hidden Markov models

1988 was an important year for the connection between AI and other fields, including statistics, operations research, decision theory, and control theory. Judea Pearl's (1988) *Probabilistic Reasoning in Intelligent Systems* led to a new acceptance of probability and decision theory in AI. Pearl's development of **Bayesian networks** yielded a rigorous and efficient formalism for representing uncertain knowledge as well as practical algorithms for probabilistic reasoning. Chapters 12 to 16 cover this area, in addition to more recent developments that have greatly increased the expressive power of probabilistic formalisms; Chapter 20 describes methods for learning Bayesian networks and related models from data.

Bayesian network

A second major contribution in 1988 was Rich Sutton's work connecting reinforcement learning—which had been used in Arthur Samuel's checker-playing program in the 1950s—to the theory of Markov decision processes (MDPs) developed in the field of operations research. A flood of work followed connecting AI planning research to MDPs, and the field of reinforcement learning found applications in robotics and process control as well as acquiring deep theoretical foundations.

One consequence of AI's newfound appreciation for data, statistical modeling, optimization, and machine learning was the gradual reunification of subfields such as computer vision, robotics, speech recognition, multiagent systems, and natural language processing that had become somewhat separate from core AI. The process of reintegration has yielded significant benefits both in terms of applications—for example, the deployment of practical robots expanded greatly during this period—and in a better theoretical understanding of the core problems of AI.

1.3.7 Big data (2001–present)

Remarkable advances in computing power and the creation of the World Wide Web have facilitated the creation of very large data sets—a phenomenon sometimes known as **big data**. These data sets include trillions of words of text, billions of images, and billions of hours of speech and video, as well as vast amounts of genomic data, vehicle tracking data, clickstream data, social network data, and so on.

Big data

This has led to the development of learning algorithms specially designed to take advantage of very large data sets. Often, the vast majority of examples in such data sets are *unlabeled*; for example, in Yarowsky's (1995) influential work on word-sense disambiguation, occurrences of a word such as "plant" are not labeled in the data set to indicate whether they

refer to flora or factory. With large enough data sets, however, suitable learning algorithms can achieve an accuracy of over 96% on the task of identifying which sense was intended in a sentence. Moreover, Banko and Brill (2001) argued that the improvement in performance obtained from increasing the size of the data set by two or three orders of magnitude outweighs any improvement that can be obtained from tweaking the algorithm.

A similar phenomenon seems to occur in computer vision tasks such as filling in holes in photographs—holes caused either by damage or by the removal of ex-friends. Hays and Efros (2007) developed a clever method for doing this by blending in pixels from similar images; they found that the technique worked poorly with a database of only thousands of images but crossed a threshold of quality with millions of images. Soon after, the availability of tens of millions of images in the ImageNet database (Deng *et al.*, 2009) sparked a revolution in the field of computer vision.

The availability of big data and the shift towards machine learning helped AI recover commercial attractiveness (Havenstein, 2005; Halevy *et al.*, 2009). Big data was a crucial factor in the 2011 victory of IBM's Watson system over human champions in the Jeopardy! quiz game, an event that had a major impact on the public's perception of AI.

1.3.8 Deep learning (2011–present)

The term **deep learning** refers to machine learning using multiple layers of simple, adjustable computing elements. Experiments were carried out with such networks as far back as the 1970s, and in the form of **convolutional neural networks** they found some success in handwritten digit recognition in the 1990s (LeCun *et al.*, 1995). It was not until 2011, however, that deep learning methods really took off. This occurred first in speech recognition and then in visual object recognition.

Deep learning

In the 2012 ImageNet competition, which required classifying images into one of a thousand categories (armadillo, bookshelf, corkscrew, etc.), a deep learning system created in Geoffrey Hinton's group at the University of Toronto (Krizhevsky *et al.*, 2013) demonstrated

a dramatic improvement over previous systems, which were based largely on handcrafted features. Since then, deep learning systems have exceeded human performance on some vision tasks (and lag behind in some other tasks). Similar gains have been reported in speech recognition, machine translation, medical diagnosis, and game playing. The use of a deep network to represent the evaluation function contributed to AlphaGo's victories over the leading human Go players (Silver *et al.*, 2016, 2017, 2018).

These remarkable successes have led to a resurgence of interest in AI among students, companies, investors, governments, the media, and the general public. It seems that every week there is news of a new AI application approaching or exceeding human performance, often accompanied by speculation of either accelerated success or a new AI winter.

Deep learning relies heavily on powerful hardware. Whereas a standard computer CPU can do 10^9 or 10^{10} operations per second. a deep learning algorithm running on specialized hardware (e.g., GPU, TPU, or FPGA) might consume between 10^{14} and 10^{17} operations per second, mostly in the form of highly parallelized matrix and vector operations. Of course, deep learning also depends on the availability of large amounts of training data, and on a few algorithmic tricks (see Chapter 21).

1.4 The State of the Art

AI Index

Stanford University's One Hundred Year Study on AI (also known as AI100) convenes panels of experts to provide reports on the state of the art in AI. Their 2016 report (Stone *et al.*, 2016; Grosz and Stone, 2018) concludes that "Substantial increases in the future uses of AI applications, including more self-driving cars, healthcare diagnostics and targeted treatment, and physical assistance for elder care can be expected" and that "Society is now at a crucial juncture in determining how to deploy AI-based technologies in ways that promote rather than hinder democratic values such as freedom, equality, and transparency." AI100 also produces an **AI Index** at aiindex.org to help track progress. Some highlights from the 2018 and 2019 reports (comparing to a year 2000 baseline unless otherwise stated):

- Publications: AI papers increased 20-fold between 2010 and 2019 to about 20,000 a year. The most popular category was machine learning. (Machine learning papers in arXiv.org doubled every year from 2009 to 2017.) Computer vision and natural language processing were the next most popular.
- Sentiment: About 70% of news articles on AI are neutral, but articles with positive tone increased from 12% in 2016 to 30% in 2018. The most common issues are ethical: data privacy and algorithm bias.
- Students: Course enrollment increased 5-fold in the U.S. and 16-fold internationally from a 2010 baseline. AI is the most popular specialization in Computer Science.
- Diversity: AI Professors worldwide are about 80% male, 20% female. Similar numbers hold for Ph.D. students and industry hires.
- Conferences: Attendance at NeurIPS increased 800% since 2012 to 13,500 attendees. Other conferences are seeing annual growth of about 30%.
- Industry: AI startups in the U.S. increased 20-fold to over 800.
- Internationalization: China publishes more papers per year than the U.S. and about as many as all of Europe. However, in citation-weighted impact, U.S. authors are 50%

ahead of Chinese authors. Singapore, Brazil, Australia, Canada, and India are the fastest growing countries in terms of the number of AI hires.

- Vision: Error rates for object detection (as achieved in LSVRC, the Large-Scale Visual Recognition Challenge) improved from 28% in 2010 to 2% in 2017, exceeding human performance. Accuracy on open-ended visual question answering (VQA) improved from 55% to 68% since 2015, but lags behind human performance at 83%.
- Speed: Training time for the image recognition task dropped by a factor of 100 in just the past two years. The amount of computing power used in top AI applications is doubling every 3.4 months.
- Language: Accuracy on question answering, as measured by F1 score on the Stanford Question Answering Dataset (SQuAD), increased from 60 to 95 from 2015 to 2019; on the SQuAD 2 variant, progress was faster, going from 62 to 90 in just one year. Both scores exceed human-level performance.
- Human benchmarks: By 2019, AI systems had reportedly met or exceeded human-level performance in chess, Go, poker, Pac-Man, Jeopardy!, ImageNet object detection, speech recognition in a limited domain, Chinese-to-English translation in a restricted domain, Quake III, Dota 2, StarCraft II, various Atari games, skin cancer detection, prostate cancer detection, protein folding, and diabetic retinopathy diagnosis.

When (if ever) will AI systems achieve human-level performance across a broad variety of tasks? Ford (2018) interviews AI experts and finds a wide range of target years, from 2029 to 2200, with a mean of 2099. In a similar survey (Grace *et al.*, 2017) 50% of respondents thought this could happen by 2066, although 10% thought it could happen as early as 2025, and a few said "never." The experts were also split on whether we need fundamental new breakthroughs or just refinements on current approaches. But don't take their predictions too seriously; as Philip Tetlock (2017) demonstrates in the area of predicting world events, experts are no better than amateurs.

How will future AI systems operate? We can't yet say. As detailed in this section, the field has adopted several stories about itself—first the bold idea that intelligence by a machine was even possible, then that it could be achieved by encoding expert knowledge into logic, then that probabilistic models of the world would be the main tool, and most recently that machine learning would induce models that might not be based on any well-understood theory at all. The future will reveal what model comes next.

What can AI do today? Perhaps not as much as some of the more optimistic media articles might lead one to believe, but still a great deal. Here are some examples:

ROBOTIC VEHICLES: The history of robotic vehicles stretches back to radio-controlled cars of the 1920s, but the first demonstrations of autonomous road driving without special guides occurred in the 1980s (Kanade *et al.*, 1986; Dickmanns and Zapp, 1987). After successful demonstrations of driving on dirt roads in the 132-mile DARPA Grand Challenge in 2005 (Thrun, 2006) and on streets with traffic in the 2007 Urban Challenge, the race to develop self-driving cars began in earnest. In 2018, Waymo test vehicles passed the landmark of 10 million miles driven on public roads without a serious accident, with the human driver stepping in to take over control only once every 6,000 miles. Soon after, the company began offering a commercial robotic taxi service.

In the air, autonomous fixed-wing drones have been providing cross-country blood deliveries in Rwanda since 2016. Quadcopters perform remarkable aerobatic maneuvers, explore buildings while constructing 3-D maps, and self-assemble into autonomous formations.

Legged locomotion: BigDog, a quadruped robot by Raibert *et al.* (2008), upended our notions of how robots move—no longer the slow, stiff-legged, side-to-side gait of Hollywood movie robots, but something closely resembling an animal and able to recover when shoved or when slipping on an icy puddle. Atlas, a humanoid robot, not only walks on uneven terrain but jumps onto boxes and does backflips (Ackerman and Guizzo, 2016).

AUTONOMOUS PLANNING AND SCHEDULING: A hundred million miles from Earth, NASA's Remote Agent program became the first on-board autonomous planning program to control the scheduling of operations for a spacecraft (Jonsson *et al.*, 2000). Remote Agent generated plans from high-level goals specified from the ground and monitored the execution of those plans—detecting, diagnosing, and recovering from problems as they occurred. Today, the EUROPA planning toolkit (Barreiro *et al.*, 2012) is used for daily operations of NASA's Mars rovers and the SEXTANT system (Winternitz, 2017) allows autonomous navigation in deep space, beyond the global GPS system.

During the Persian Gulf crisis of 1991, U.S. forces deployed a Dynamic Analysis and Replanning Tool, DART (Cross and Walker, 1994), to do automated logistics planning and

scheduling for transportation. This involved up to 50,000 vehicles, cargo, and people at a time, and had to account for starting points, destinations, routes, transport capacities, port and airfield capacities, and conflict resolution among all parameters. The Defense Advanced Research Project Agency (DARPA) stated that this single application more than paid back DARPA's 30-year investment in AI.

Every day, ride hailing companies such as Uber and mapping services such as Google Maps provide driving directions for hundreds of millions of users, quickly plotting an optimal route taking into account current and predicted future traffic conditions.

MACHINE TRANSLATION: Online machine translation systems now enable the reading of documents in over 100 languages, including the native languages of over 99% of humans, and render hundreds of billions of words per day for hundreds of millions of users. While not perfect, they are generally adequate for understanding. For closely related languages with a great deal of training data (such as French and English) translations within a narrow domain are close to the level of a human (Wu *et al.*, 2016b).

SPEECH RECOGNITION: In 2017, Microsoft showed that its Conversational Speech Recognition System had reached a word error rate of 5.1%, matching human performance on the Switchboard task, which involves transcribing telephone conversations (Xiong *et al.*, 2017). About a third of computer interaction worldwide is now done by voice rather than keyboard; Skype provides real-time speech-to-speech translation in ten languages. Alexa, Siri, Cortana, and Google offer assistants that can answer questions and carry out tasks for the user; for example the Google Duplex service uses speech recognition and speech synthesis to make restaurant reservations for users, carrying out a fluent conversation on their behalf.

RECOMMENDATIONS: Companies such as Amazon, Facebook, Netflix, Spotify, YouTube, Walmart, and others use machine learning to recommend what you might like based on your past experiences and those of others like you. The field of recommender systems has a long history (Resnick and Varian, 1997) but is changing rapidly due to new deep learning methods that analyze content (text, music, video) as well as history and metadata (van den Oord *et al.*, 2014; Zhang *et al.*, 2017). Spam filtering can also be considered a form of recommendation (or dis-recommendation); current AI techniques filter out over 99.9% of

spam, and email services can also recommend potential recipients, as well as possible response text.

Game playing: When Deep Blue defeated world chess champion Garry Kasparov in 1997, defenders of human supremacy placed their hopes on Go. Piet Hut, an astrophysicist and Go enthusiast, predicted that it would take "a hundred years before a computer beats humans at Go—maybe even longer." But just 20 years later, AlphaGo surpassed all human players (Silver *et al.*, 2017). Ke Jie, the world champion, said, "Last year, it was still quite human-like when it played. But this year, it became like a god of Go." AlphaGo benefited from studying hundreds of thousands of past games by human Go players, and from the distilled knowledge of expert Go players that worked on the team.

A followup program, AlphaZero, used no input from humans (except for the rules of the game), and was able to learn through self-play alone to defeat all opponents, human and machine, at Go, chess, and shogi (Silver *et al.*, 2018). Meanwhile, human champions have been beaten by AI systems at games as diverse as Jeopardy! (Ferrucci *et al.*, 2010), poker (Bowling *et al.*, 2015; Moravčík *et al.*, 2017; Brown and Sandholm, 2019), and the video games Dota 2 (Fernandez and Mahlmann, 2018), StarCraft II (Vinyals *et al.*, 2019), and Quake III (Jaderberg *et al.*, 2019).

IMAGE UNDERSTANDING: Not content with exceeding human accuracy on the challenging ImageNet object recognition task, computer vision researchers have taken on the more difficult problem of image captioning. Some impressive examples include "A person riding a motorcycle on a dirt road," "Two pizzas sitting on top of a stove top oven," and "A group of young people playing a game of frisbee" (Vinyals *et al.*, 2017b). Current systems are far from perfect, however: a "refrigerator filled with lots of food and drinks" turns out to be a no-parking sign partially obscured by lots of small stickers.

MEDICINE: AI algorithms now equal or exceed expert doctors at diagnosing many conditions, particularly when the diagnosis is based on images. Examples include Alzheimer's disease (Ding *et al.*, 2018), metastatic cancer (Liu *et al.*, 2017; Esteva *et al.*, 2017), ophthalmic disease (Gulshan *et al.*, 2016), and skin diseases (Liu *et al.*, 2019c). A systematic review and meta-analysis (Liu *et al.*, 2019a) found that the performance of AI programs, on average, was equivalent to health care professionals. One current emphasis in medical AI is in facilitating human–machine partnerships. For example, the Lyna system achieves 99.6%

overall accuracy in diagnosing metastatic breast cancer—better than an unaided human expert—but the combination does better still (Liu *et al.*, 2018; Steiner *et al.*, 2018)..

The widespread adoption of these techniques is now limited not by diagnostic accuracy but by the need to demonstrate improvement in clinical outcomes and to ensure transparency, lack of bias, and data privacy (Topol, 2019). In 2017, only two medical AI applications were approved by the FDA, but that increased to 12 in 2018, and continues to rise.

CLIMATE SCIENCE: A team of scientists won the 2018 Gordon Bell Prize for a deep learning model that discovers detailed information about extreme weather events that were previously buried in climate data. They used a supercomputer with specialized GPU hardware to exceed the exaop level (10^{18} operations per second), the first machine learning program to do so (Kurth *et al.*, 2018). Rolnick *et al.* (2019) present a 60-page catalog of ways in which machine learning can be used to tackle climate change.

These are just a few examples of artificial intelligence systems that exist today. Not magic or science fiction—but rather science, engineering, and mathematics, to which this book provides an introduction.

1.5 Risks and Benefits of AI

Francis Bacon, a philosopher credited with creating the scientific method, noted in *The Wisdom of the Ancients* (1609) that the "mechanical arts are of ambiguous use, serving as well for hurt as for remedy." As AI plays an increasingly important role in the economic, social, scientific, medical, financial, and military spheres, we would do well to consider the hurts and remedies—in modern parlance, the risks and benefits—that it can bring. The topics summarized here are covered in greater depth in Chapters 27 and 28.

To begin with the benefits: put simply, our entire civilization is the product of our human intelligence. If we have access to substantially greater machine intelligence, the ceiling on our ambitions is raised substantially. The potential for AI and robotics to free humanity from menial repetitive work and to dramatically increase the production of goods and services could presage an era of peace and plenty. The capacity to accelerate scientific research could result in cures for disease and solutions for climate change and resource shortages. As Demis Hassabis, CEO of Google DeepMind, has suggested: "First solve AI, then use AI to solve everything else."

Long before we have an opportunity to "solve AI," however, we will incur risks from the misuse of AI, inadvertent or otherwise. Some of these are already apparent, while others seem likely based on current trends:

- **LETHAL AUTONOMOUS WEAPONS:** These are defined by the United Nations as weapons that can locate, select, and eliminate human targets without human intervention. A primary concern with such weapons is their *scalability*: the absence of a requirement for human supervision means that a small group can deploy an arbitrarily large number of weapons against human targets defined by any feasible recognition criterion. The technologies needed for autonomous weapons are similar to those needed for self-driving cars. Informal expert discussions on the potential risks of lethal autonomous weapons began at the UN in 2014, moving to the formal pre-treaty stage of a Group of Governmental Experts in 2017.
- **SURVEILLANCE AND PERSUASION:** While it is expensive, tedious, and sometimes legally questionable for security personnel to monitor phone lines, video camera feeds, emails, and other messaging channels, AI (speech recognition, computer vision, and

natural language understanding) can be used in a scalable fashion to perform mass surveillance of individuals and detect activities of interest. By tailoring information flows to individuals through social media, based on machine learning techniques, political behavior can be modified and controlled to some extent—a concern that became apparent in elections beginning in 2016.

- **BIASED DECISION MAKING:** Careless or deliberate misuse of machine learning algorithms for tasks such as evaluating parole and loan applications can result in decisions that are biased by race, gender, or other protected categories. Often, the data themselves reflect pervasive bias in society.
- **IMPACT ON EMPLOYMENT:** Concerns about machines eliminating jobs are centuries old. The story is never simple: machines do some of the tasks that humans might otherwise do, but they also make humans more productive and therefore more employable, and make companies more profitable and therefore able to pay higher wages. They may render some activities economically viable that would otherwise be impractical. Their use generally results in increasing wealth but tends to have the effect of shifting wealth from labor to capital, further exacerbating increases in inequality. Previous advances in technology—such as the invention of mechanical looms—have resulted in serious disruptions to employment, but eventually people find new kinds of work to do. On the other hand, it is possible that AI will be doing those new kinds of work too. This topic is rapidly becoming a major focus for economists and governments around the world.
- **SAFETY-CRITICAL APPLICATIONS:** As AI techniques advance, they are increasingly used in high-stakes, safety-critical applications such as driving cars and managing the water supplies of cities. Fatal accidents have already occurred and highlight the difficulty of formal verification and statistical risk analysis for systems developed using machine learning techniques. The field of AI will need to develop technical and ethical standards at least comparable to those prevalent in other engineering and healthcare disciplines where people's lives are at stake.
- **CYBERSECURITY:** AI techniques are useful in defending against cyberattack, for example by detecting unusual patterns of behavior, but they will also contribute to the potency, survivability, and proliferation capability of malware. For example, reinforcement learning methods have been used to create highly effective tools for automated, personalized blackmail and phishing attacks.

We will revisit these topics in more depth in Section 27.3. As AI systems become more capable, they will take on more of the societal roles previously played by humans. Just as humans have used these roles in the past to perpetrate mischief, we can expect that humans may misuse AI systems in these roles to perpetrate even more mischief. All of the examples given above point to the importance of governance and, eventually, regulation. At present, the research community and the major corporations involved in AI research have developed voluntary self-governance principles for AI-related activities (see Section 27.3). Governments and international organizations are setting up advisory bodies to devise appropriate regulations for each specific use case, to prepare for the economic and social impacts, and to take advantage of AI capabilities to address major societal problems.

What of the longer term? Will we achieve the long-standing goal: the creation of intelligence comparable to or more capable than human intelligence? And, if we do, what then?

Human-level AI

Artificial general intelligence (AGI)

For much of AI's history, these questions have been overshadowed by the daily grind of getting AI systems to do anything even remotely intelligent. As with any broad discipline, the great majority of AI researchers have specialized in a specific subfield such as game-playing, knowledge representation, vision, or natural language understanding—often on the assumption that progress in these subfields would contribute to the broader goals of AI. Nils Nilsson (1995), one of the original leaders of the Shakey project at SRI, reminded the field of those broader goals and warned that the subfields were in danger of becoming ends in themselves. Later, some influential founders of AI, including John McCarthy (2007), Marvin Minsky (2007), and Patrick Winston (Beal and Winston, 2009), concurred with Nilsson's warnings, suggesting that instead of focusing on measurable performance in specific applications, AI should return to its roots of striving for, in Herb Simon's words, "machines that think, that learn and that create." They called the effort **human-level AI** or HLAI—a

machine should be able to learn to do anything a human can do. Their first symposium was in 2004 (Minsky *et al.*, 2004). Another effort with similar goals, the **artificial general intelligence (AGI)** movement (Goertzel and Pennachin, 2007), held its first conference and organized the *Journal of Artificial General Intelligence* in 2008.

Artificial superintelligence (ASI)

At around the same time, concerns were raised that creating **artificial superintelligence** or **ASI**—intelligence that far surpasses human ability—might be a bad idea (Yudkowsky, 2008; Omohundro, 2008). Turing (1996) himself made the same point in a lecture given in Manchester in 1951, drawing on earlier ideas from Samuel Butler (1863):[15]

15 Even earlier, in 1847, Richard Thornton, editor of the *Primitive Expounder*, railed against mechanical calculators: "Mind ... outruns itself and does away with the necessity of its own existence by inventing machines to do its own thinking. ... But who knows that such machines when brought to greater perfection, may not think of a plan to remedy all their own defects and then grind out ideas beyond the ken of mortal mind!"

> It seems probable that once the machine thinking method had started, it would not take long to outstrip our feeble powers. ... At some stage therefore we should have to expect the machines to take control, in the way that is mentioned in Samuel Butler's *Erewhon*.

These concerns have only become more widespread with recent advances in deep learning, the publication of books such as *Superintelligence* by Nick Bostrom (2014), and public pronouncements from Stephen Hawking, Bill Gates, Martin Rees, and Elon Musk.

Experiencing a general sense of unease with the idea of creating superintelligent machines is only natural. We might call this the **gorilla problem**: about seven million years ago, a now-extinct primate evolved, with one branch leading to gorillas and one to humans. Today, the gorillas are not too happy about the human branch; they have essentially no control over their future. If this is the result of success in creating superhuman AI—that humans cede control over their future—then perhaps we should stop work on AI, and, as a corollary, give up the benefits it might bring. This is the essence of Turing's warning: it is not obvious that we can control machines that are more intelligent than us.

Gorilla problem

If superhuman AI were a black box that arrived from outer space, then indeed it would be wise to exercise caution in opening the box. But it is not: *we* design the AI systems, so if they do end up "taking control," as Turing suggests, it would be the result of a design failure.

To avoid such an outcome, we need to understand the source of potential failure. Norbert Wiener (1960), who was motivated to consider the long-term future of AI after seeing Arthur Samuel's checker-playing program learn to beat its creator, had this to say:

> If we use, to achieve our purposes, a mechanical agency with whose operation we cannot interfere effectively ... we had better be quite sure that the purpose put into the machine is the purpose which we really desire.

Many cultures have myths of humans who ask gods, genies, magicians, or devils for something. Invariably, in these stories, they get what they literally ask for, and then regret it. The third wish, if there is one, is to undo the first two. We will call this the **King Midas problem**: Midas, a legendary King in Greek mythology, asked that everything he touched should turn to gold, but then regretted it after touching his food, drink, and family members.[16]

16 Midas would have done better if he had followed basic principles of safety and included an "undo" button and a "pause" button in his wish.

King Midas problem

We touched on this issue in Section 1.1.5, where we pointed out the need for a significant modification to the standard model of putting fixed objectives into the machine. The solution to Wiener's predicament is not to have a definite "purpose put into the machine" at all. Instead, we want machines that strive to achieve human objectives but know that they don't know for certain exactly what those objectives are.

It is perhaps unfortunate that almost all AI research to date has been carried out within the standard model, which means that almost all of the technical material in this edition reflects that intellectual framework. There are, however, some early results within the new framework. In Chapter 16, we show that a machine has a positive incentive to allow itself to be switched off if and only if it is uncertain about the human objective. In Chapter 18, we formulate and study **assistance games**, which describe mathematically the situation in which a human has an objective and a machine tries to achieve it, but is initially uncertain about what it is. In Chapter 22, we explain the methods of **inverse reinforcement learning** that allow machines to learn more about human preferences from observations of the choices that humans make. In Chapter 27, we explore two of the principal difficulties: first, that our choices depend on our preferences through a very complex cognitive architecture that is hard to invert; and, second, that we humans may not have consistent preferences in the first place—either individually or as a group—so it may not be clear what AI systems *should* be doing for us.

Assistance game

Inverse reinforcement learning

Summary

This chapter defines AI and establishes the cultural background against which it has developed. Some of the important points are as follows:

- Different people approach AI with different goals in mind. Two important questions to ask are: Are you concerned with thinking, or behavior? Do you want to model humans, or try to achieve the optimal results?
- According to what we have called the standard model, AI is concerned mainly with **rational action**. An ideal **intelligent agent** takes the best possible action in a situation. We study the problem of building agents that are intelligent in this sense.
- Two refinements to this simple idea are needed: first, the ability of any agent, human or otherwise, to choose rational actions is limited by the computational intractability of doing so; second, the concept of a machine that pursues a definite objective needs to be replaced with that of a machine pursuing objectives to benefit humans, but uncertain as to what those objectives are.
- Philosophers (going back to 400 BCE) made AI conceivable by suggesting that the mind is in some ways like a machine, that it operates on knowledge encoded in some internal language, and that thought can be used to choose what actions to take.
- Mathematicians provided the tools to manipulate statements of logical certainty as well as uncertain, probabilistic statements. They also set the groundwork for understanding computation and reasoning about algorithms.
- Economists formalized the problem of making decisions that maximize the expected utility to the decision maker.
- Neuroscientists discovered some facts about how the brain works and the ways in which it is similar to and different from computers.
- Psychologists adopted the idea that humans and animals can be considered information-processing machines. Linguists showed that language use fits into this model.
- Computer engineers provided the ever-more-powerful machines that make AI applications possible, and software engineers made them more usable.
- Control theory deals with designing devices that act optimally on the basis of feedback from the environment. Initially, the mathematical tools of control theory were quite different from those used in AI, but the fields are coming closer together.

- The history of AI has had cycles of success, misplaced optimism, and resulting cutbacks in enthusiasm and funding. There have also been cycles of introducing new, creative approaches and systematically refining the best ones.
- AI has matured considerably compared to its early decades, both theoretically and methodologically. As the problems that AI deals with became more complex, the field moved from Boolean logic to probabilistic reasoning, and from hand-crafted knowledge to machine learning from data. This has led to improvements in the capabilities of real systems and greater integration with other disciplines.
- As AI systems find application in the real world, it has become necessary to consider a wide range of risks and ethical consequences.
- In the longer term, we face the difficult problem of controlling superintelligent AI systems that may evolve in unpredictable ways. Solving this problem seems to necessitate a change in our conception of AI.

Bibliographical and Historical Notes

A comprehensive history of AI is given by Nils Nilsson (2009), one of the early pioneers of the field. Pedro Domingos (2015) and Melanie Mitchell (2019) give overviews of machine learning for a general audience, and Kai-Fu Lee (2018) describes the race for international leadership in AI. Martin Ford (2018) interviews 23 leading AI researchers.

The main professional societies for AI are the Association for the Advancement of Artificial Intelligence (AAAI), the ACM Special Interest Group in Artificial Intelligence (SIGAI, formerly SIGART), the European Association for AI, and the Society for Artificial Intelligence and Simulation of Behaviour (AISB). The Partnership on AI brings together many commercial and nonprofit organizations concerned with the ethical and social impacts of AI. AAAI's *AI Magazine* contains many topical and tutorial articles, and its Web site, aaai.org, contains news, tutorials, and background information.

The most recent work appears in the proceedings of the major AI conferences: the International Joint Conference on AI (IJCAI), the annual European Conference on AI (ECAI), and the AAAI Conference. Machine learning is covered by the International Conference on Machine Learning and the Neural Information Processing Systems (NeurIPS) meeting. The major journals for general AI are *Artificial Intelligence*, *Computational Intelligence*, the *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *IEEE Intelligent Systems*, and the *Journal of Artificial Intelligence Research*. There are also many conferences and journals devoted to specific areas, which we cover in the appropriate chapters.